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Quantifying and understanding land cover changes by large and small oil palm expansion regimes in the Peruvian Amazon

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ABSTRACT

With rapid increases in global food demand and production, oil palm expansion constitutes a major emerging challenge for forest conservation in Amazonia and other tropical forest regions. This threat is evident in the Peruvian Amazon, where local and national incentives for oil palm cultivation along with growing large-scale investments translate into accelerated oil palm expansion. Environmental sustainability of oil palm cultivation in the Peruvian Amazon is contingent on policy incentives for expansion onto already-cleared lands instead of biodiverse, high carbon primary rainforests. Previous research indicates that while industrial plantations use less land area than local smallholders, companies have a higher tendency to expand into primary rainforests. However, the motivations behind these differing expansion scenarios remain unclear. In this study we combine data from optical and radar satellite sensors with training information, field discussions, and review of public documents to examine the policy incentives and spatial patterns associated with oil palm expansion by smallholders and industries in one of Peru's most rapidly changing Amazonian landscapes: the Ucayali region of the city of Pucallpa. Based on our satellite-based land cover change analysis, we found that between 2010 and 2016, smallholders utilized 21,070 ha more land area for oil palm than industries but industrial expansion occurred predominantly in old growth forests (70%) in contrast to degraded lands for smallholders (56%). Our analysis of national policies related to oil palm expansion reveal policy loopholes associated with Peru's "best land use" classification system that allow for standing forests to undergo large-scale agricultural development with little government oversight. We conclude that both sectors will need careful, real-time monitoring and government engagement to reduce old-growth forest loss and develop successful strategies for mitigating future environmental impacts of oil palm expansion.

1. Introduction

As the pressure of contemporary trends in globalization, climate change, consumption and population rise continues on Earth's limited land resources, efforts to understand and monitor the underlying social, economic, and political incentives and ecological consequences of land cover changes are vital at local to global scales (Lambin and Geist, 2006). Land use decisions such as the allocation of industrial-scale agriculture play a central role in driving cropland expansion patterns, posing a serious challenge for the conservation of critical ecosystems around the world. Current projections estimate a 14% increase in global agricultural land between 2010 and 2030, constituting an increasing pressure on old growth forests and other ecosystems (Schneider et al., 2011).

Palm oil production illustrates how rising widespread global agricultural demands are increasingly impacting tropical forest cover. During the past few decades, oil palm (*Elaeis guineensis*) has become one of the most highly expanding equatorial crops in the world, grown in over 43 countries and utilizing nearly one-tenth of the world's permanent cropland (Koh and Wilcove, 2008). The rapid growth of oil palm plantations can be linked directly to a rising global demand for vegetables oils: in the last fifty years, global demand for the product has grown exponentially and is expected to double by 2030 as population and average incomes increase (Carter et al., 2007). Additionally, oil palm produces the largest oil output for the smallest amount of land—the average oil yield for oil palm is over 4 times the one for any of the other leading oilseeds like soybean, sunflower, and rapeseed (Potts et al., 2014).

Despite oil palm's productivity and land efficiency, oil palm expansion can contribute to large environmental impacts such as deforestation, peat and watershed degradation, biodiversity loss, and forest

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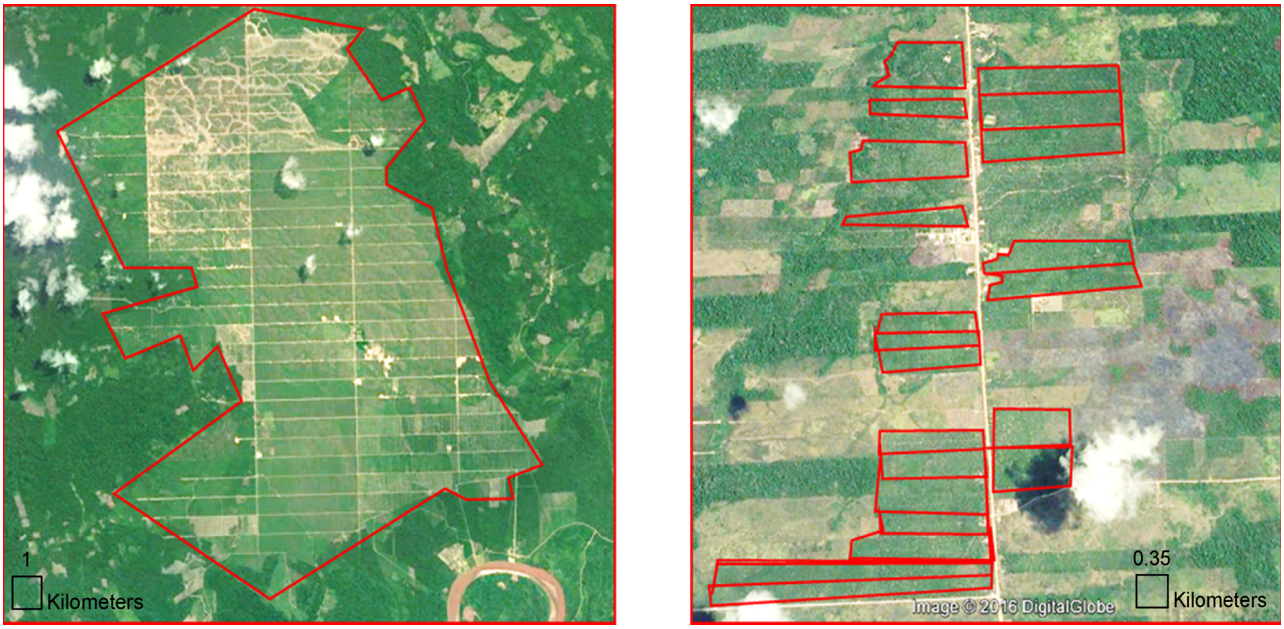

Fig. 1. Industrial (left) versus smallholder expansion patterns. Note the scale in the left image is bigger than the right. Source: Google Earth, 2016.

fires (Wilcove and Koh, 2010). The draining of peatlands, slash-and-burn forest clearing practices for new plantations, and other methods of agricultural expansion, when quantified, result in net positive global carbon emissions (Carlson et al., 2012). Given unprecedented growth of oil palm production and expansion, efforts to minimize the environmental footprint of agricultural development through targeted financial mechanisms such as the UN initiative for Reducing Carbon Emissions from Deforestation and Forest Degradation (REDD) must meet their goals through close monitoring of expansion practices and carbon changes, especially in the richly biodiverse tropics.

Most of the global area suitable for oil palm cultivations is currently within tropical forests with deep, flat, permeable soils 10 degrees north and south of the equator (Murphy, 2014; FAO, 1983). Oil palm production is recognized as a major driver of deforestation in regions such as Southeast Asia, where more than 80% of the world's palm oil is produced (Abood et al., 2015). With rapid increases in global land use for oil palm production, oil palm plantations have quickly spread to South America's Amazon tropical forest region (Butler and Laurance, 2009). Presently, Amazonian countries comprise 60% of the tropical area suitable for oil palm (Persson and Azar, 2010) and the practice has been actively promoted by local governments in lands associated with primary rainforests (Pacheco, 2012). Among the countries that comprise Amazonia, Peru has the second largest forest area suitable for oil palm plantations (Stickler et al., 2007). Rising global demand, national political support, and economic incentives for oil palm production in South America all constitute increasing threats to forest conservation in areas like Peru, which still retains a high proportion of forest cover relative to developed lands and with low historical deforestation rates (Da Fonseca et al., 2007).

On a national scale, the Peruvian government has publicly promoted the cultivation of oil palm as an economic alternative to illegal drug trafficking after publically declaring oil palm as a cultivation of national interest in 2000. Political incentives for oil palm in Peru include tax exemptions for investments in oil palm production and a mandate to mix 5% biodiesel in diesel oils (USDA GAIN Report, 2012). While the government has put incentives for oil palm production in place, in 2014 the national government also signed a letter of intent for "Zero Net Deforestation" with Germany and Norway, committing to increasing five million hectares of forested titles to indigenous peoples on lands which they hold legal, communal, or customary rights to ensure those tenure rights are respected and forests are protected (Joint Declaration of Intent, 2014).

In order to minimize impacts to forests as industrial plantations enter the Western Hemisphere, the future environmental performance of oil palm in the Peruvian Amazon is contingent on political incentives for expansion onto cleared lands instead of highly biodiverse tropical forests (Gutierrez-Velez and Defries, 2013). Methods to monitor and map real-time oil palm expansion between large and small stakeholders provide vital tools to spatially assess the successes of such political incentives and ecological outcomes. Earlier work has shown that map-based information on both the natural controls and ecosystem threats to carbon density affords targeted interventions to reduce greenhouse gas emissions in developing tropical nations (Asner et al., 2014a). Thus, understanding the area change from land conversions to oil palm by different acting regimes are equally crucial to ultimately promote better forest management policies in the future.

Previous research efforts have focused on monitoring and mapping oil palm expansion in the Peruvian Amazon region in order to help identify carbon and forest loss from the expansion patterns of different regimes of production (Asner et al., 2014b; Gutierrez-Velez et al., 2011). In Peru, two models of oil palm expansion occur. The first, defined as industrial expansion, is normally operated by private companies who have access to enough capital and technology to invest in optimizing higher yields over larger extensions of lands. Smallholder plantations are those operated mostly by local farmers with more restricted access to capital and land, often producing lower yields. (Gutierrez-Velez et al., 2011). Well-defined uniformly sized geometric shapes and road infrastructure are characteristic of industrial regimes, while smallholder plantations are normally clustered along main access roads with variable shapes and sizes typically ranging between 5 to 10 ha, rarely exceeding 20 ha (Bruinsma, 2009, Fig. 1).

Using remote sensing to classify expansion patterns and map the conversion of land covers to oil palm over a period of 10 years (2000–2010), Gutierrez-Velez et al. (2011) found that while industrial plantations use less land area than local smallholders, plantation companies have a higher tendency to expand into primary rainforests. If the effects of expansion are quantified further, this result could mean that in the Peruvian Amazon, industrial oil palm production occurs at a higher expense than smallholder groups for forest conservation. However, recent differences in the landscape impacts between the two

regimes of production in the Ucayali region have yet to be studied.

Beyond the impacts of oil palm expansion on deforestation, it is equally vital to understand how ambiguities in the Peruvian land tenure policy might incentivize oil palm operations on previously forested lands. Despite their importance, the specific socio-political drivers of industrial-scale expansion into mostly old-growth forests versus smallholder expansion into already cleared lands is still widely unclear and unresolved.

Presently in Peru, in order to legally gain authorization for the development of forests for agricultural purposes, palm oil companies must be granted approval according to the Ministry of Agriculture's (MINAGRI) Best Land Use Capacity for Agriculture (BLUC) parameters of land use classification. However, loopholes exist in these measures, as some groups rely on a technical classification of the land that ignores the presence of standing trees when evaluating requests for land use change. As long as forests remain officially unclassified, tracts of primary rainforest are authorized for development, blurring the lines between illegal and legal deforestation of primary rainforests for oil palm (EIA Report, 2015). Disputed claims to property over forests, officially owned by the state, could be an important driver of the resulting expansion of oil palm into rainforests, however these direct causes are still unknown.

In this paper, we analyze policy incentives, spatial patterns, and ecological impacts of oil palm expansion by comparing smallholder and industrial regimes of agricultural production through a combination of field measurements, remote sensing, GIS, and literature review in the Ucayali region surrounding the city of Pucallpa, one of Peru's most dynamic deforestation hotspots. We extend and update previous work by Gutierrez-Velez et al. (2011) by classifying and mapping Pucallpa's current 2016 land covers through satellite imagery and field data in order to assess if the expansion tendencies of the two regimes into primary rainforests and degraded lands remain. By citing anecdotal evidence in the field along with the review of recent literature of published literature, government documents, and investigations, we contribute to fill a causal research gap by not only visualizing *how* these differing stakeholders expand, but also helping to explain *why*. Thus, alongside our visualized outcomes, we pose the following policy question: What socio-political incentives are motivating the resulting oil palm expansion patterns between smallholder and industrial production regimes, and how can we use this to inform sustainable land use planning through avoided deforestation in the Peruvian Amazon? Our analysis results are used to underscore future policy strategies for sensible oil palm cultivation and land allocation policy regionally, nationally, and internationally.

2. Methods

2.1. Study area

The study area constitutes a rapidly evolving landscape, located in the Peruvian eastern district of Ucayali. This area has seen a dramatic increase in the amount of total land area harvested for agriculture, matching global trends in oil palm production (Oliveira et al., 2007, Fig. 2). This region along with the district of San Martin, are responsible for 98% of the total area used for oil palm in Peru (Ministerio de Agricultura, 2011). The study centers on a focus area of 5792 km^2 in the Ucayali Region, located between the Aguaytia and Ucayali rivers near the city of Pucallpa. This region is located in a largely dynamic deforestation hotspot, where previous research has identified the active presence of both industrial-scale and smallholder regimes of oil palm plantations (Gutierrez-Velez et al., 2011). Ucayali currently comprises 35% of Peru's oil palm in production and is one of the departments with the highest rate of deforestation in the country (Bennett et al., 2018a).

The terrain is a mix of undulated degraded plains and knoll hills that do not pose large strains on the production of oil palm in regards to soil drainage, slope, or flooding (GOREU-IIAP, 2003). Elevations oscillate between 150 and 250 m above sea level and an annual mean temperature of around 25 °C, with fluctuations ranging between 21 and 32 °C. Precipitation is bimodal, ranging from 1500 to 2500 mm/yr with a longer dry season between June and August and a shorter one in December (Barbaran-Garcia, 2000 and Fujisaka et al., 2000).

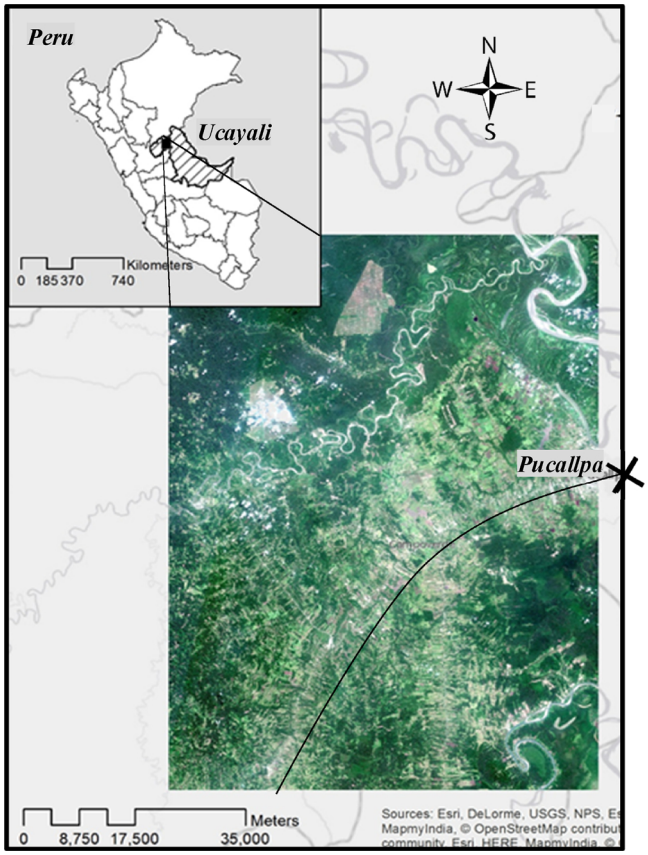

Fig. 2. Map of study region west of the city of Pucallpa between the Ucayali and Aguaytia rivers in the Ucayali district of Peru displaying the raw Sentinel-2 satellite imagery with natural color 432 band combination used as input for the 2016 classification.

2.2. Land cover classification and change detection (LCC)

We measured the conversion of different land covers to smallholder and industrial oil palm plantations over the past six years (2010–2016) by classifying recent images from the European Space Agency, 2016 Sentinel satellite system. We then compared our resulting 2016 classification with a previously classified map for the region from 2010 (Gutierrez-Velez and Defries, 2013). Satellite data input variables for the 2016 classification were downloaded for preprocessing, which included three mosaicked scenes from SENTINEL-2 A (optical 10 m resolution Level-1C product) and two scenes from SENTINEL-1 SAR (C-BAND radar imagery at 10 m resolution and VH/VV polarization Standard L1) (Table 1).

Sentinel-2 bands were stacked, mosaicked, and clipped to fit the extent of the study area. The downloaded images had a minimal cloud coverage (< 1%) for the June-August 2016 time period, when field data was collected. A cloud mask was produced manually by drawing polygons of "No Data" around the few clouds and cloud shadows present in the images. The VH and VV polarized Sentinel-1 Products were also clipped to match the area extent. Geometric correction was deemed unnecessary upon visual comparison of the Sentinel scenes and Google Earth high-resolution imagery, which were co-registered closely. Atmospheric or radiometric correction was not necessary because all the images from each sensor were from the same date and the

Table 1
Detailed list of spatial data sets used in the analysis, all projected under the coordinate system UTM 18 S, WGS 1984.

	Format	Unique ID / Tile Number	Date	Native Pixel Size	Processing Level & Polarization	Source
Sentinel-2A	Raster	Tile #: T18LWR	August 4, 2016	10 m*	LEVEL-1C	Copernicus Scientific Hub, 2016
Sentinel-2A	Raster	Tile #: T18LWR	August 4, 2016	10 m*	LEVEL-1C	Copernicus Scientific Hub, 2016
Sentinel-2A	Raster	Tile #: T18LVR	August 4, 2016	10 m*	LEVEL-1C	Copernicus Scientific Hub, 2016
Sentinel-2A	Raster	Tile #: T18MWS	August 4, 2016	10 m*	LEVEL-1C	Copernicus Scientific Hub, 2016
Sentinel-1	Raster	ID: 681D	September 12, 2016	10 m	SAR Standard L1 (GRD) & VH	Copernicus Scientific Hub, 2016
Sentinel-1	Raster	ID: 859D	September 12, 2016	10 m	SAR Standard L1 (GRD) & VH	Copernicus Scientific Hub, 2016
Google Earth Points	Vector (from KML)		2016			Google Earth, 2016
Study Area	Vector shapefile		2016			Hand-drawn

* These tiles included all Sentinel-2 bands with a native pixel size of 10-m: Bands B2 (490 nm), B3 (560 nm), B4 (665 nm) and B8 (842 nm).

classification did not involve any extrapolation in space or time (Song et al., 2001).

For oil palm, the neatly lined monoculture plantations starkly differ from mixed old-growth forests, and thus the texture outputs are vital to improve the classification and spectral separability of oil palm. To incorporate the Sentinel-1 data in the classification, a texture analysis was computed for the downloaded scene using a Co-Occurrence Based Filter implemented in the ENVI program (Exelis Visual Information Solutions, Boulder, Colorado). This filter uses a co-occurrence matrix to calculate texture values as a function of both the angular relationship and distance between pixels, ultimately showing the number of occurrences of the relationship between a pixel and its specified eight neighboring pixels for a user-determined processing window (Anys et al., 1994). The filter types include mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation, which each contain their own equations for computing texture values (Haralick et al., 1973).

Homogeneity, contrast, entropy, and variance were chosen as the texture inputs for classification and subsequently stacked on top of the cloud-corrected Sentinel-2 optical bands. A processing window of 21 × 21 was used following the approach used by Carolita et al., 2015 who found that using a kernel size of 21 pixels yielded more precise classification results separating oil palm than a smaller window. All textural outputs were re-projected to match Sentinel-2's pixel resolution and coordinate system corresponding to WGS 1984 UTM zone 18 (Fig. 3).

We obtained the geo-location of areas covered by oil palm for the 2016 classification and validation through field visits to oil palm operations and forest areas between the months of June and July in 2016. Field-based reference data was based on an opportunistic access-based sampling of 550 points and polygons distributed evenly along all major roads in the landscape along with photographs taken with an integrated camera/GPS receiver and compass in areas representative of land covers of interest that used supplementary geospatial information from previous land zoning studies. Land covers consisted of water (rivers and lakes), un-vegetated (bare soils, roads, built environment, sand banks), pasture (*pasto*), fallow/shrublands (*purma baja*), primary forests (*purma alta*), secondary forests, burn scars, and oil palm plantations, categorized in three age ranges: immature < 5 years, juvenile 5–10 years, and adult > 10 years). Sampling in oil palm field included notation of the approximate age, ownership, and total size of the plantations based on visual inspection and information by owner or manager at the time of measurement.

Land cover classification for 2016 was performed using a Maximum Likelihood supervised classification method implemented in the ENVI software (Exelis Visual Information Solutions, Boulder, Colorado). This method assumes that the spectral properties for each class in each band are normally distributed. It then characterizes a class by the mean vector and the covariance matrix and computes the statistical probability to determine the membership of the cell to the class (Richards, 1999). Post classification consisted on the application of a majority filter with a 3 × 3 window to reduce noise and remove isolated misclassified pixels.

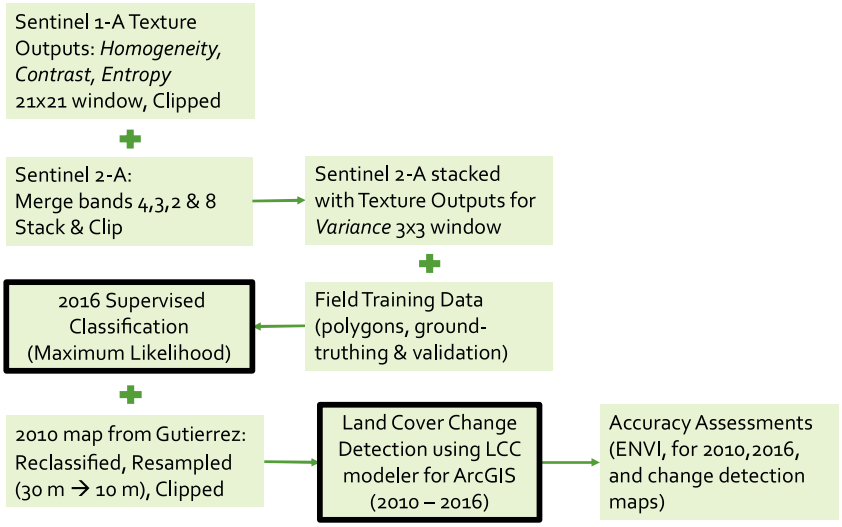
Sentinel 1-A Texture Outputs: Homogeneity, Contrast, Entropy 21x21 window, Clipped
Sentinel 2-A: Merge bands 4,3,2 & 8 Stack & Clip
Sentinel 2-A stacked with Texture Outputs for Variance 3x3 window
2016 Supervised Classification (Maximum Likelihood)
Field Training Data (polygons, ground-truthing & validation)
2010 map from Gutierrez: Reclassified, Resampled (30 m → 10 m), Clipped
Land Cover Change Detection using LCC modeler for ArcGIS (2010 – 2016)
Accuracy Assessments (ENVI, for 2010, 2016, and change detection maps)

Fig. 3. Workflow of exploratory methodology for combining Sentinel-1 and Sentinel-2 2016 data to perform supervised classification, land cover change, and accuracy assessment using a 2010 map and LCC for ArcGIS.

Classification accuracy for the 2016 classification map was assessed by setting aside a third of the ground data collected in the field for the calculation of kappa coefficient and commission and omission errors. Land cover change detection was performed by comparing the 2016 classified map with a previously classification for 2010 by Gutierrez-Velez et al. (2011). For that purpose, the 2010 map was reclassified by age of plantations to match the oil palm age groups (immature, juvenile, and adult) used in the 2016 map. The 2010 image was clipped and resampled to align it with the 10-meter resolution of the 2016 map. The accuracy assessment of change was calculated as a joint probability of detecting non-oil palm categories in 2010 and oil palm categories in 2016. This transition was calculated as a product of those probabilities.

The 2010 and 2016 classification maps were entered as inputs in the Land Change Modeler (LCM) for ArcGIS extension 2 (Clark Labs, Clark University, Worcester, MA) to quantify the number of pixels converted to different land cover classes. Two different land cover change maps were made—the first used the original 2010 and 2016 maps and all the 11 land cover categories as inputs to calculate total land area conversions for all classes over the six-year timeframe. The second land cover change map was made using reclassified images of the two maps as input with simplified classes: secondary forest, old growth forest, degraded lands (all other non-oil palm classes) and the three age classes of oil palm by regime (smallholder or industrial). The second map was to facilitate the delineation of the expansion by the two modes of production into forested or degraded lands. Following the approach used by Gutierrez-Velez and DeFries (2013), large and small regimes of plantations were discerned based on visual inspection, rigorous ground-truthing, verbal consent with land-owners and workers, as well as documentation from the field and plantation site visits (Fig. 1).

2.3. Socio-political interest analysis

A comprehensive literature review of journal articles, government documents, and investigative reports were compiled and analyzed to gain understanding about the possible socio-political incentives, motivating factors, or barriers that might have influenced the contrasting expansion outcomes by the two regimes. This analysis was complemented with anecdotal evidence from the field to provide further context about the possible political, economic, or social causes of the visualized and quantified oil palm expansion patterns.

3. Results

3.1. Land cover map in 2016

The use of Senitnel-2 A and Sentinel-1 A data for oil palm classification in 2016 resulted in an overall accuracy of 88% with a kappa coefficient of 0.82. (Fig. 4). The accuracy assessment matrix consolidated land covers into oil palm (all age classes), old growth forest, secondary forest, and degraded (fallow, pasture, shrub) since this was the main focus of landscape transition during this period. The total area classified as oil palm in all age classes in the 2016 map was 55,159 ha. This corresponds to 10% of the total land area of 579,200 ha. The 2010 map, using the same consolidate land cover classes, yielded an overall accuracy of 92% with a kappa coefficient of 0.88 (Table 2). The 2016 land classification yielded an overall error percentage of 12%. The most accurately classified land cover was secondary forest, and the lowest corresponded to degraded land covers, possibly due to the variety of spectral signatures (Table 3).

3.2. Land cover change detection (2010–2016)

To effectively and efficiently visualize the landscape dynamics of oil palm we grouped major changes in land covers from 2010 to 2016 into old-growth primary forests, degraded lands (which included all remaining non-oil palm classes), and the aggregate of all three oil palm age classes delineated by production regimes (smallholder and industrial) in the land cover change map (Fig. 5). Insets show detailed close-ups of both production regimes, reflecting larger areas of forests converted into industrial plantation blocks and higher utilization of

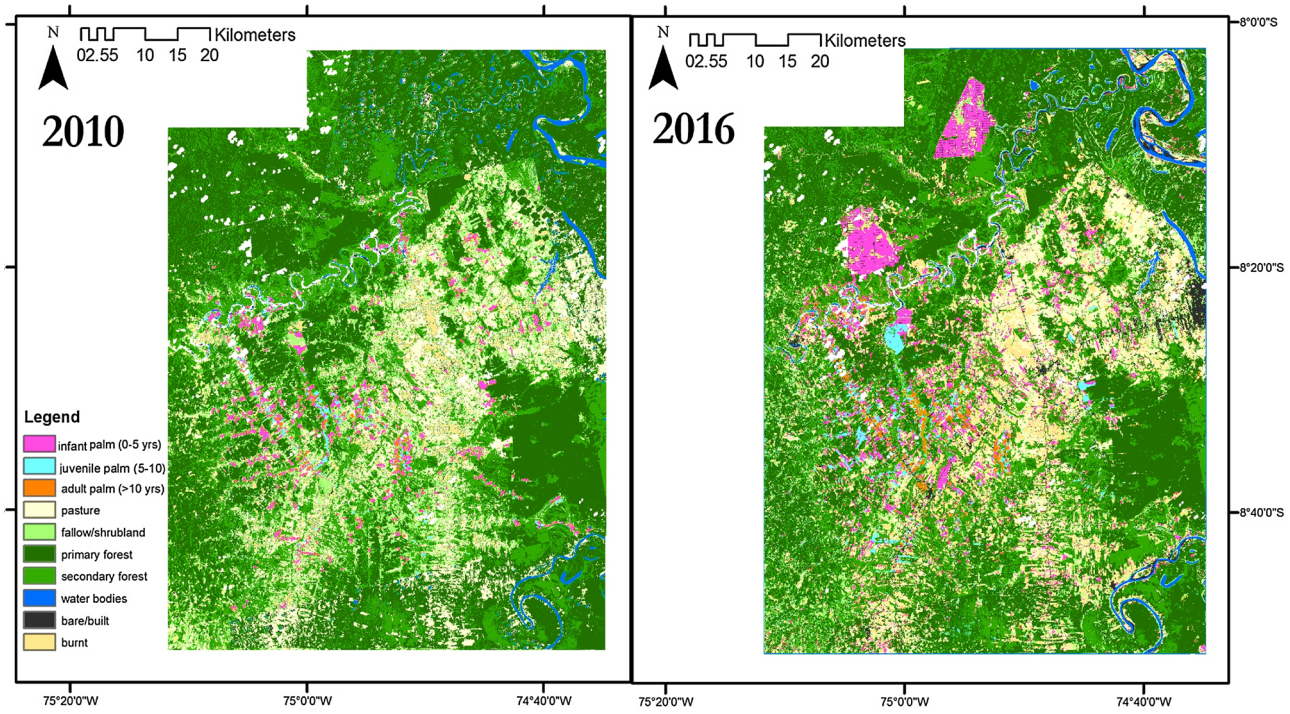

Fig. 4. Maximum Likelihood Classification between 2010 and 2016 using Sentinel-2 and Sentinel-1 A texture outputs (homogeneity, contrast, and entropy for Sentinel-1 and variance for Sentinel-2). The 2010 map was classified using Landsat and ALOS/PALSAR. Shows significant oil palm expansion in the six-year period. Regions in white represent unclassified pixels.

Table 2
Error Matrix in the 2010 classification using Landsat and ALOS/PALSAR with an overall error of 8%.

Accuracy Assessment 2010				
Overall Accuracy: 92% Kappa Coefficient: 0.88				
	Palm	Degraded	Secondary	Old growth
Palm	85.72	9.03	3.80	0.01
Degraded	11.41	89.16	5.42	0.02
Secondary	2.69	1.77	85.60	1.95
Old growth	0.17	0.04	5.18	98.03
Total	100	100	100	100

Table 3
Error Matrix in the 2016 classification using Sentinel-1 and Sentinel-2 with an overall error of 12%.

Accuracy Assessment 2016				
Overall Accuracy: 88% Kappa Coefficient: 0.82				
	Oil palm	Degraded	Secondary	Old growth
Oil palm	88.61	10.81	0.00	0.00
Degraded	3.80	81.08	0.00	4.55
Secondary	0.00	0.00	100.00	0.00
Old growth	7.59	8.11	0.00	95.45
Total	100	100	100	100

degraded lands by smallholder plantations along major roads. The results of the accuracy assessment of change show that old growth transitions to oil palm yielded the highest accuracy, while secondary forest transitions yielded the lowest accuracy. However, overall the transitions were well-balanced, all containing an accuracy of more than 75% (Fig. 6).

In our land use change area calculations, we distinguished secondary forest from degraded (pasture and fallow) classes. Although the aggregate expansion of smallholder regimes covered a larger overall land area than industrial—35,000 ha versus 14,000 ha, or around 2.5 times more land area, only 26% of the land area used by smallholders was originally old-growth forest compared to 70% of the industrial expansion (Fig. 7). The majority of the aggregate smallholders utilized degraded lands or secondary forests (55% and 18% respectively). Only 13% of industrial expansion was classified as previously degraded, indicating differences in the proportion of different land covers converted into oil palm by the two production regimes.

An important consideration in comparing the two regimes is that within the study region around Pucallpa there are around 200 smallholder individual or cooperative associations, averaging 5–10 hectares a plot, whereas within the study area we noted only seven official industrial plantations. In this regard, the bigger industrial plantations are outnumbered by smallholdings. Even though more area is expanded by the aggregate smallholders, the average area occupied by large individual oil palm holdings is much larger than smallholder operations. Also, the smallholder holdings had a larger proportion of land classified as adult palm than industrial, which contained majority immature palm. The proportionality of land covers occupied by the two regimes provides an important indicator for the environmental cost of a given unit of oil palm per actor type. These structural patterns of land use also provide an assessment for the projected increases in oil palm production under both types of production. Considering that most industrial plantations were fairly new and young, this proportional viewpoint contains important information for anticipating the impact of future development to the region's biodiversity and carbon landscape if current trends in expansion continue.

4. Discussion

4.1. PART I – measuring current modes of expansion and their impacts on deforestation

4.1.1. Implications for forest conservation and biodiversity

The land cover change map by production regime supports the original hypothesis: while smallholders as a whole tended to use more land area for production of oil palm, industrial plantations tended to expand mostly into primary forests. This pattern of expansion has marked implications for both carbon and biodiversity conservation as old-growth forests contain tall carbon-dense canopies of diverse species (Rödig et al., 2017).

Measuring land cover legacies through remote sensing offers salient information for understanding the contribution of agricultural development and forest conservation (Schwartz et al., 2017). In old growth forests, carbon dioxide is stored in live woody tissues and slowly decomposing organic matter in litter and soil. Contrary to long-standing views of carbon neutrality, old-growth forests can continue to accumulate carbon in large quantities for centuries if left undisturbed (Luyssaert et al., 2008). Large-scale expansion of oil palm has been a main driver of old growth forest conversion in other tropical areas (Carlson et al., 2013). Studies have shown that in Peru, since subsistence and larger scale agriculture drive much of the deforestation, prices of commodities like oil palm determine the opportunity costs of deforestation (Ravikumar et al., 2017a). Our findings demonstrate that in Peru, industrial plantations proportionally utilize more primary forests for oil palm agriculture, threatening their net carbon balance. Therefore, if unchecked, this production group can be a threat for forest stability and carbon permanence in the Peruvian Amazon. Deforestation is already the largest driver of emissions from land use change, which is the second largest anthropogenic source of carbon dioxide globally (Le Quéré et al., 2018).

The area of old-growth forests converted to oil palm in our study also have marked implications for the conservation of biodiversity in the landscape. Oil palm plantations support much fewer species than forests and other tree crops, fragment habitat zones and corridors, and can contribute to pollution of waterways for aquatic life through pesticides and fertilizers (Vijay et al., 2016). Fitzherbert et al. (2008) for instance, found that across all taxa observed, a mean of only 15% of species recorded in primary forest were also found in oil palm plantations, and mostly consisted of generalists and pests. More recent research also suggests that oil palm is particularly poor habitat for birds in Western Amazonia, driving a decline in avifaunal species of higher conservation value (Srinivas and Koh, 2016). When successfully implemented, land use planning tools for oil palm certification such as REDD can work in tandem to mitigate agricultural impacts on both carbon stock and biodiversity through avoided deforestation, exhibiting direct covariance for high-resolution data (Deere et al., 2018).

4.1.2. Remote sensing methodology & accuracy

The availability of data from the recently launched, high spatial resolution, open-source Sentinel satellite imagery collection constitutes an opportunity to combine passive optical and active radar data to describe land cover changes attributed to oil palm expansion at different spatial scales and geographic domains. However, since the technology is fairly new, 10-meter spatial-resolution studies such as this one can only describe changes from 2014 onward—earlier dates would require high resolution imagery that is costly or at a less precise coarser resolution. Complementing optical imagery with texture analysis improved the delineation of oil palm from surrounding forests or other agricultural lands, and has been used in other successful oil palm studies in the past (Gutierrez-Velez and DeFries, 2011; Santos and Messina, 2008; Tan et al., 2013). The combination of variance, homogeneity, contrast, and entropy texture outputs successfully identified oil palm in many areas with relatively larger errors in the differentiation

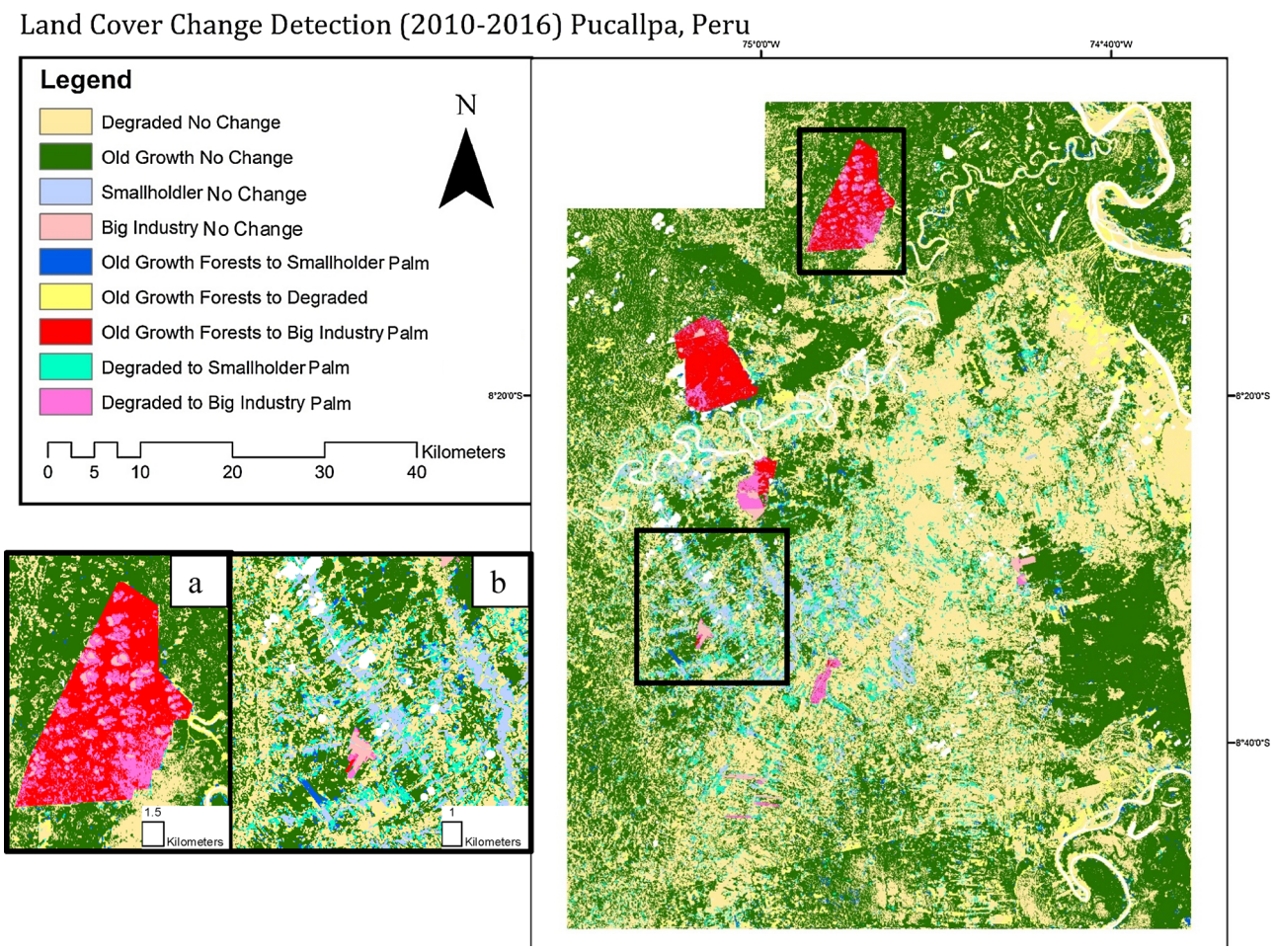

Fig. 5. Land Cover Change Detection from 2010 to 2016 in Pucallpa, Peru using the categories of Degraded, Old Growth Forests, Industrial Palm, and Smallholder Palm. (a) shows a close-up of an industrial plantation, showing majority of expansion onto old-growth forests, while (b) indicates smallholder expansion into degraded zones.

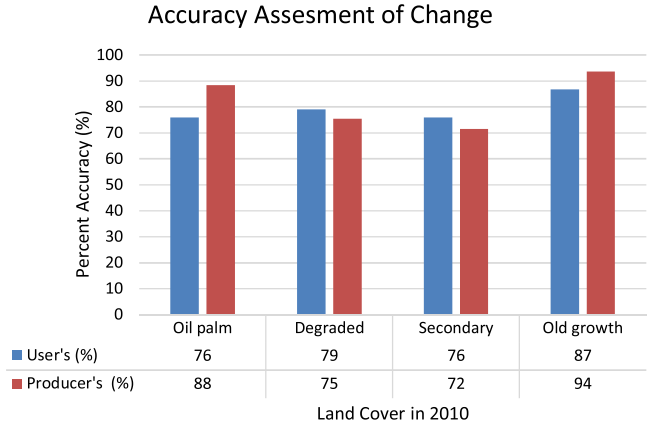

Fig. 6. Accuracy Assessment of Change from each consolidated land cover category to oil palm.

between age classes of oil palm (immature, juvenile, adult). Future studies should apply more tailored classification approaches (decision-tree, object based classifications, NDVI thresholds) in order to improve accuracy further from the current precision of 88%.

Other sources of information, such as the L band instead of the C band for the radar inputs, could improve classification results for the 2016 map. Differences in the ability to discriminate oil palm using L band versus C band data might help to explain the 4% difference in the overall accuracy between the 2010 (92%) and 2016 (88%) maps. The radar imagery used in the 2010 classification came from L band ALOS/PALSAR radar imagery, while only C band imagery was available for the finer-scale Sentinel-1 radar data in 2016. The L band better captures the complexity of the vertical structure of vegetation and their textural heterogeneity, thus distinguishing oil palm and forest canopies to a greater degree. The C band has a lower capacity to penetrate the canopy of the landscape, so there is a higher risk for confusion between the oil palm and forest classes (Teng et al., 2015). The incorporation of time series information to discriminate land cover categories each year could provide a more robust analysis of the expansion patterns as well, as it has been demonstrated in previous publications (Gutierrez-Velez and DeFries, 2013). Finally, matching land cover changes with spatially explicit carbon estimates through biomass measurements at the pixel level could help to understand the quantified landscape tradeoffs through carbon flux.

4.2. PART II - socio-political analysis of incentives for land use outcomes

4.2.1. Motivating factors for smallholder expansion

During the past two decades, the increase in smallholder oil palm cultivation is mostly attributed to alternative development projects to replace previous coca cultivation, creating what has been coined as the "United Nations (UN) model" or "supported smallholders" due the massive influx of institutional funding through government incentive programs as well as international development projects such as the

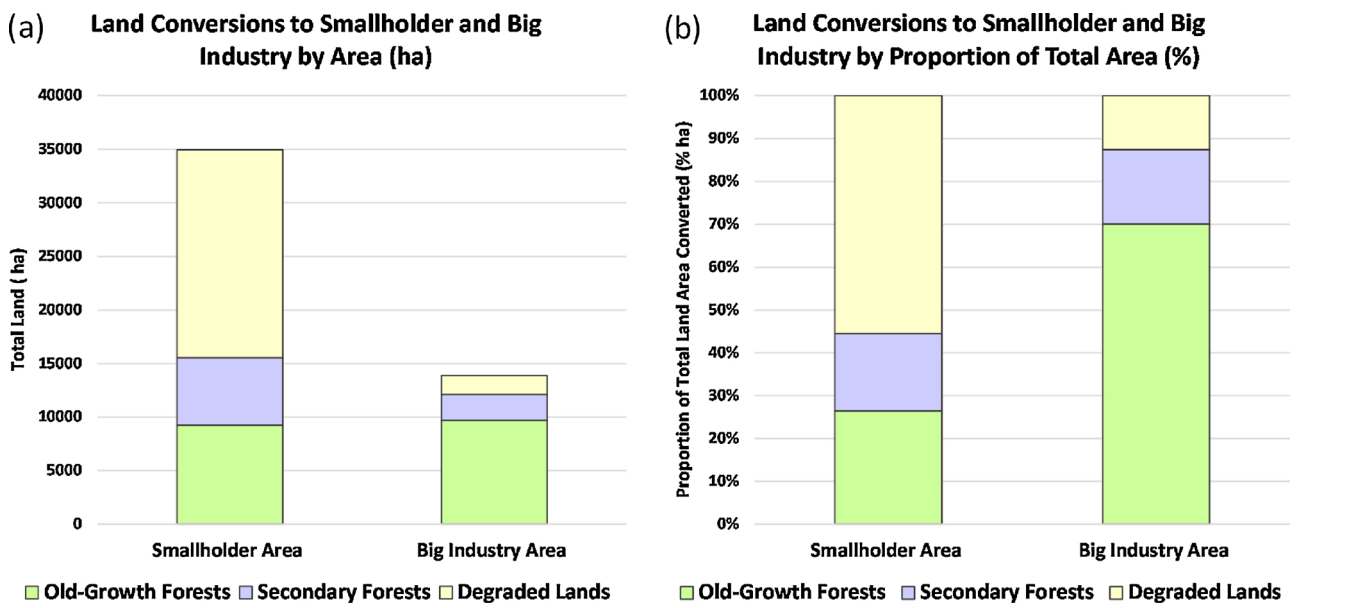

Fig. 7. Conversion to Smallholder and Industrial Regimes from 2010 to 2016 in Pucallpa, Peru by (a) Total Area (ha) and (b) Proportion of Total Area (%), indicating more land area used by smallholders but proportionally more primary forest expansion by industrial regimes.

UNDP (Bennett et al., 2018b). Many family-run oil palm farms receive financial assistance via seedlings, fertilizer, and technical assistance on credit with the condition that oil palm is planted outside primary forests (Gobierno Regional de Ucayali, 2008). This can help explain why most newly emerged oil palm cultivations for smallholder collectives are located on previously cultivated lands of yucca, cacao, and coca. Current investments under this model now cover about half of the total national area planted for oil palm (Bello, 2017).

Smallholders collectively promote oil palm by creating various associations of local smallholder growers and leveraging NGO funds to build collective processing mills and crop supplies. In Ucayali, Comité Central de Palmicultores de Ucayali (Central Committee of Oil Palm Growers of Ucayali – COCEPU) is the main smallholder organization in our landscape of study, owning the middle-sized processing company OLAMSA (Oleaginosas Amazónicas). As a non-profit civil association, COCEPU does not divide income among members, but gives services like seeds, fertilizers, and nurseries to participating farmers. Farmers receive cash from selling their fruits to the OLAMSA mill, and farmers who are also stockholders receive shares of the company's yearly profits (Bello, 2017). However, most oil palm associations under the UN Model target local farmers with formal land titles, and formal property rights are frequently a prerequisite for smallholders to secure loans (such as from the Inter-American Development Bank) for participation in agricultural development projects (De Soto, 2000).

Our results show that smallholders proportionally utilized more degraded lands for oil palm expansion. However, in absolute terms, deforestation by smallholders is around the same magnitude as large holders. Land titling policies might constitute perverse incentives for deforestation among smallholders. Since land titling is crucial to participation in the growing number of oil palm development projects, a complicating factor arose when a 2008 national decree established that smallholders "must demonstrate economic exploitation" of land in order to qualify for official titling, which includes clearing forest, or "preparation of the land for planting" (Supreme Decree 032-, 2008). Thus gaining property rights can inevitably encourage deforestation, since only non-forest lands can be officially owned. Recent research also found that land titling campaigns favor areas where oil palm is being adopted, therefore persuading neighboring cultivators to follow suit (Bennett et al., 2018a).

Overall trends in land use for smallholders in the Peruvian Amazon are much less straightforward than homogenous industrial regimes. For instance, while the path to land titling may pressure certain local groups to clear lands, a portion of independent smallholders still lack any formal claims and illegally continue to cultivate oil palm (Pacheco et al., 2017). Contemporary discussions and documents in Peru tend to highlight small-scale agriculture as the main driver of deforestation. Nevertheless, recent work has found this overarching claim to be conflated and based on the frequency of remotely-sensed forest patches cleared without any supplementary field data on the ground to support their motivations (Ravikumar et al., 2017b). Thus, we highlight different distinctive characteristics in Pucallpa's surrounding smallholdings in order to possibly shed a more focused light on their visualized and field-based expansion outcomes.

Unlike industrial monoculture projects, many small farmers in Amazonia practice dynamic, seasonal subsistence cultivation on long-term landholdings that are highly dependent on family needs and size (Ravikumar et al., 2017b). This means that crops flux according to changing seasons, income sources, and collective neighboring land-use, creating a shifting equilibrium of land use between forests, crops, and fallow systems (Marquardt et al., 2013). Deforestation events in smallholdings are often the result of forestlands temporarily leased by villagers when neighbors need extra space for fallowing due to the addition of new family members, which is then returned to the owner to fallow for re-use (Bennett et al., 2018a). This localized trend of land recycling helps explain the large proportion of degraded area expanded on by smallholders for oil palm. The mapped results show most categorized smallholdings as aging adult palm with any new, infant expansion clustered close-by. This supports literature that found that small deforestation events in the Peruvian Amazon by local family production systems are often the result of periodic clearing of up to 5 ha of forest to rotate or expand an already productive area, supporting a more stable and longstanding pattern of cyclic land use (Ravikumar et al., 2017b). However, while these traditional rotational farming practices complement ongoing forest regeneration through fallowing, recent literature highlights that these systems may be in danger of disappearing under newer intensified models (Coomes et al., 2017).

Indeed, for specifically high-yield perennial crops like oil palm, government and NGO promoted projects have influenced some farmers, especially ones new to the area, to convert systems to intensified single-use plantations. However, literature suggests that the intensification of

land from perennial crops like oil palm, despite their efficiency, do not equate to land sparing in Ucayali (Porro et al., 2015). The expansion outcomes of intensified smallholder monocultures may be better explained by the proximity to the closest processing mill, since fresh fruit bunches (FFB) must be processed within 48 h of harvesting (Furumo and Aide, 2017). Depending on if the mill is surrounded by forest or near other agricultural lands, this may determine whether deforested or degraded land is targeted.

Recent literature has also explored a newer and quickly growing mode of oil palm production in Peru, the Company-Community Partnership (CCP). This model involves a private or state-owned company "partnering" under a contractual agreement with local smallholder villages to share land, capital, management and market opportunities by collectively renting or ceding a percentage of their land to the larger company in exchange for a portion of the profits. Since 2013, the CCP model has been promoted as a more equitable and sustainable strategy under the assumption that greater productivity, smallholder integration, and efficient intensified land use on smallholder farms will decrease the overall deforestation impact. However, a new study has found little evidence for positive environmental outcomes in these newer models of privately-run shared ownership schemas, with CCP farms exhibiting more deforestation than neighboring non-oil palm farms due to the displacement of traditional rotational subsistence farms and colonization of new forest areas (Bennett et al., 2018b). In order to join the CCP, smallholder plots are often bought out and 'given' elsewhere in the forest frontier as private companies absorb their older plots to establish their shared plantation area.

Thus, since smallholder regimes are so varied, in order to better understand at-large motivations to deforest the entire cultivation history needs to be studied on a full seasonal rotation at each farm in conjunction with nearby smallholdings that may be in collaboration. There is also potential for temporal lags in the conversion of forests to oil palm by smallholders due to high capital costs or temporary rotations. Further studies between these two regimes could focus on investigating the magnitude of indirect land use change or conversion lags. This type of work would require finer resolution data to identify other cultivation types over a longer period of time and be complemented with field interviews.

In addition, documenting individual titling statuses will further inform recent deforestation patterns after 2008, since the decree requires a demonstrated economic exploitation of land before the official recognition of a property is granted. Lastly, the presence of larger, intensified oil palm projects (both private partnerships and government-funded) need to be considered as this may have a larger effect on how neighboring farms utilize their surrounding landscape resources. Industrial plantations, once established, may be having a pressuring effect that triggers diversified farm mosaics to deforest near its edges as newer roads are established and further settlers are attracted to the region (Bello, 2017). Understanding the diverse modes of smallholder production (subsistence and cash, UN-model, CCP) as well as the political processes that form them are critical to forming a more nuanced view of smallholder land use planning and environmental outcomes in the future.

4.2.2. Industrial expansion motivations

Unlike smallholders, the collective characteristics of industrial actors show many more commonalities in structure, size, and management. Large, industrial-scale plantations have sufficient capital to produce higher yields, and ownership is often extra-local and corporate-owned. For example, the Melka Group, an international network of companies, has over 25 developments operating in Ucayali and other Peruvian districts, mostly in oil palm (EIA Report, 2015). Plantaciones de Ucayali and de Pucallpa are both shown in our northern study region (Fig. 4, right panel), with official dates of establishment listed as November 2010, just months after the 2010 satellite image and corresponding land classification map were obtained (ibid.).

Unlike smallholders, proximity to commercial processing mills and subsequently the roads that connect them are not a limiting factor for industrial plantations. Companies can use their capital to construct roads and on-site processing mills wherever they are needed (Furumo and Aide, 2017). This can result in industrial plantation establishments far beyond the smallholder agricultural frontier, penetrating remote areas that most likely involve forest removal. A previous model of rent for forest and agricultural land use theorizes that the increase in access costs for big oil palm companies could offset the lessened costs to defend property rights, since state forces are weaker in more remote regions (Angelsen, 2007). Thus, isolated concessions established in wilderness areas are made more profitable, likely motivating these actors to expand onto primary and secondary forests for their production. Considering that two-thirds of globally suitable area left for oil palm exists on areas of high carbon stock forest (> 100 t AGB), the lack of non-forested land suitable for growth could help to explain the choice of forested lands as the development sites for the more recently established industrial oil palm companies in this region (Pirker et al., 2016).

In Peru and the districts such as Ucayali, it is apparent that policy incentives for the observed expansion patterns of industrial plantations are based on weak government enforcement of national policies surrounding land classification and allocation for development (EIA Report, 2015; Furumo and Aide, 2017). The presence of large, homogenous, state-owned areas viable for large cultivation are assumed to lead extra-local and internationally-sourced companies to target them for expansion, thus avoiding degraded lands with frequently disputed land tenure (Gutierrez-Velez et al., 2011). We explore the possible national and regional regulatory structures largely responsible for permitting these deforestation practices below.

4.2.3. Peruvian regulatory framework for agricultural land governance

Differences in the proportion of oil palm expansion into different land covers of the two production regimes could be explained in part by the regulatory structure around land use. In Peru, there are two main laws and accompanying regulatory frameworks that establish governance over agricultural and forested lands split between three different agencies: The Ministry of Agriculture and Irrigation (**MINAGRI**), the Ministry of Environment (**MINAM**), and the regional governments. The first regulatory framework, named the ***Land & Agriculture Laws***, aim to govern land tenure and agricultural production for both communal and private individual property rights. Founded in the Land Law of 1995 (*Ley de Tierras No, 26505*) and implemented by MINAGRI, it establishes procedures for allocation of public lands into agriculture where the *capacidad de uso mayor de la tierra* (Best Land Use Capacity, or BLUC) has been classified as agriculture or livestock production.

The second law, ***Forestry and Wildlife Law*** (*Ley N°, 29763*), was approved by the Peruvian Congress in 2011 and is in the process of being implemented. It establishes that public lands with a best land use capacity determined to be forest should be conserved in their natural state as *Bosques de Produccion Permanente* (Permanent Production Forests). Deforestation or conversion to agriculture is prohibited on these lands with enforced reforestation measures imposed if altered in any way. Lands that are especially ecologically fragile are classified as *Bosques Permanentes de Proteccion* (Permanent Protection Forests) and are not eligible to be classified for any other use (timber, agriculture, soil removal for mining) (Legislacion Forestal y de Fauna Silvestre, 2015).

The land classification system used by the Ministry of Agriculture (MINAGRI) to develop agro-ecological zoning (*Zonificación Agro-Ecológica* – ZAE) is consultative with local communities, but focuses on maximizing the utility of landscapes for productive activities without any strict environmental or social criteria. Thus, it has been employed by some private companies as an isolated technical procedure to permit the development of plantations. (Helms, 1992; USAID Report, 2015). The Ministry of the Environment (MINAM) has a separate land-use planning process intended to support sustainable development of

natural resources through participative and legally-binding technical landscape zoning studies (*Zonificación Ecológica Económica* – ZEE) which are intended to complement the ZAE with additional land use information beyond just crop production, such as biodiversity, watershed management, mineral reserves, and local populations. However, the development of ZEEs is led by independent research institutes. These zoning studies have not been officially completed for all Peruvian districts despite their promotion for over 20 years. No current ZEE exists for the district of Ucayali since 2000.

The split authority between MINAGRI's ZAEs and MINAM's ZEEs creates a legal loophole that permits the conversion of forested lands to oil palm plantations for both small and large producers. MINAGRI's BLUC classification is defined as the natural capacity of the land to be productive in a permanent fashion, under certain uses and procedures. BLUC classifies land into only five categories—intensive cultivation, permanent cultivation, pastures, forestry, and protection—and these definitions are determined by just two indicators: soil characteristics and climatic conditions (Dirección General de Asuntos Ambientales Agrarios (DGAAA), 2016). The land cover (ie: living trees) is not considered relevant to the BLUC methodology, despite its two categories of forestry and protection.

In effect, MINAGRI's BLUC omits the presence of standing trees in its methodology. If the best land use capacity (BLUC) is determined to be some form of agriculture, its management can side-step the jurisdiction of the Ministry of the Environment and legally deforest. Out of the 74 million hectares of Peruvian forests, only 54 million acres have been charted by official studies, without any maps of distribution and no reference to the other 20 million hectares of standing forest (EIA Report, 2015). Thus, these remaining 20 million hectares of forest remain vulnerable to BLUC assessments that could define them as agricultural land for development.

While this route of land acquisition for oil palm is possible, the actual obtainment of these forested lands stands in direct violation with the national forest patrimony stated in the Forest and Wildlife Law (Supreme Decree 017-, 2009-AG). For example, the law states that those who have title to authorization certificates (*títulos habilitantes*) of forest concessions must abide by the corresponding management plan approved by the regional forestry and wildlife authority. In our study region in July 2014, the regional government imposed administrative sanctions against two large plantations after clearing 4,000 ha of forest without the required land use change authorization by the Ucayali forest authority despite their declaration of zero non-compliant land clearing (Executive Directoral Resolution, 2014; Finer and Novoa, 2015). As a result, the Roundtable for Sustainable Palm Oil (RSPO) issued a stop-work order in one of the companies, which subsequently put their property up for sale that same year, before any production had even begun (Plantaciones de Pucallpa, 2018 RSPO case tracker).

In order to avoid future illegal deforestation and seek more sustainable routes of production on Peruvian lands, it is thus important to understand how loopholes in BLUC definitions that ignore standing trees contribute to the resulting expansion outcomes large-scale oil palm. In this region it is unlikely to find large swaths of degraded land available, making it costly and logistically challenging to purchase multiple properties from enough adjacent individual owners to make the plantation economically viable and efficient, given that industrial plantation tend to maximize yields in homogeneous blocks of monocultures (USAID Report, 2015). Regional governments could support and oversee community-based land titling initiatives in the Amazon like the Ucayali Titling and Communal Reserve Project to promote participatory land planning in zones of low conservation value to ease the burden of purchasing adjacent previously titled land. Restrictions to expand into forests and compliance mechanisms for both regimes of production should also be set in place privately in the supply chain, such as through accredited environmental auditing organizations like the RSPO. Currently Peru has only six RSPO members, making up less than 1% of its worldwide partnerships.

5. Conclusions

Large industries and smallholders ultimately differ in their expansion strategies into degraded lands and old-growth rainforests for oil palm production. This work helps to understand long-term environmental effects of oil palm expansion by extending the time-series of previously mapped land use change in Pucallpa, Peru into the present. The land cover change map from 2010 to 2016 by production regime reinforce the previous mapped findings from Gutierrez-Velez et al. (2011) and provide further evidence about the implications of such patterns of expansion for deforestation. Although smallholders converted more land area for production of oil palm as a whole, their land use as a proportion of total area converted tells a different story. By utilizing more degraded lands for cultivation, they avoided converting more than 40% forested land than big industries in the region (Fig. 7b).

Our methods combining active and passive remote sensing to describe land cover legacies can be used to better understand the contribution of forests to carbon mitigation strategies such as the REDD carbon credit allocation program and to establish mechanisms to make it competitive compared to the profit associated with oil palm production. The review of policy incentives for expansion identifies governmental loopholes that could indirectly incentivize large-scale oil palm expansion into forest. However, further studies should include formal surveys of social responses as well as agronomic investigations of land cover contribution to oil palm cultivation in order to gain a full perspective of expansion motives between smallholders and large producers. Reducing pressure of large-scale plantations on forests could involve creating country-wide systematized and transparent criteria for land use classification (BLUCs), improving inter-sectoral coordination between regional, environment, and agriculture ministries, and supporting government regulated community-based land zoning initiatives to promote forest conservation through cultivations on degraded lands, which result in net sequestration by the time oil palm reaches maturity. These results have the potential to translate into policy changes that bolster the information needed to make effective land use planning decisions in the Peruvian government.

6. Policy recommendations

Promoting sustainable oil palm agriculture and land use planning in the Peruvian Amazon in the future could be benefited from simplifying the complex, contradictory regulatory framework regarding agriculture and forestry by mandating intersectoral coordination between the regional forestry service, Ministry of the Environment, and MINAGRI's BLUC classification schema. Such simplification would entail the integration in the Agro-ecological Zoning (ZAE) and Ecologic-Economic Zoning (ZEE) processes into one single set of agricultural-conservation based criteria. Governmental financial incentives on programs to support production regimes utilizing already-degraded lands for oil palm production over primary or secondary forests could also contribute to reduce the pressure of oil palm expansion into forests.

Our work demonstrates the feasibility for the implementation of a land use change monitoring system. Such implementation along with publicly available records of authorized operations could help identify and deter illegal land clearing. This could enable the local actors to help regulate activity and promote compliance among oil palm investors. The public could support transparency in land use planning through participatory community mapping projects, or by making ZEE land zoning and tenure information available in GIS format on open access web portals like Global Forest Watch or Google Earth Engine.

More importantly, the inclusion of standing trees as a primary indicator in determining the five categories for the BLUC system would help accurately distinguish forests from agricultural or degraded landscapes (Furumo and Aide, 2017). This would require field visits by the competent authorities (such as the Dirección General de Asuntos Ambientales Agrarios, DGAAA, 2016) to areas under consideration for

land use change. Until these policies are actually set in place however, government at the national and regional levels are in a position to implement a moratorium on the allocation of lands owned by the state or with undefined tenure to agricultural projects until Best Capacity Land Use maps officially exist for regional districts.

Lastly, international assistance programs in Peru should prioritize the security and protection of forests by closely monitoring forest changes for potential violations to treaties and regional laws. These foreign countries could further emphasize previous national commitments on net-zero deforestation agreements as political leverage to help these BLUC reform policies develop in a more time-sensitive manner, and broaden RSPO's reach and expedite membership within Peru to ensure sustainable production in the future.

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